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Real-time Assessment of Upper Extremity Motor Function in Stroke Patients Using Machine Learning

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Abstract – This paper proposes a novel AI-based system that leverages a smartphone camera to assess upper limb motor functions in stroke survivors, following the National Institute of Health Stroke Scale (NIHSS) guidelines. Accurate assessment of motor functions is crucial for effective stroke rehabilitation, yet current methods often require direct involvement from healthcare professionals, who may be in short supply even in developed countries. Designed for remote and autonomous rehabilitation, our system enables patients or their attendants to conduct assessment exercises using only a smartphone. The AI algorithm evaluates motor function based on NIHSS scoring criteria, helping to address the shortage of healthcare professionals in clinical settings. The system employs Mediapipe Pose to extract 33 skeletal features from the camera feed, arranging these in a sequential manner using the sliding window technique, which enhances temporal analysis. These keypoints are then analyzed by machine learning models (SVM, KNN, RF, and MLP), which were trained on publicly available stroke rehabilitation datasets, including UI-PRMD and TRSP. The models achieved impressive average accuracies of 95.27%, 94.62%, 96.90%, and 95.94%, respectively. By providing real-time, NIHSS-aligned assessments of motor functions, this application has the potential to reduce the burden on healthcare professionals, increase accessibility to rehabilitation services, and ultimately improve patient outcomes during the recovery process.

Keywords – Stroke Rehab, NIHSS, AI-Augmented, RGB Camera, Machine Learning.

I. INTRODUCTION

Stroke is a chronic disease that has severe consequences on its survivor's life; it is among the leading causes of disabilities worldwide [1]. In the majority of cases, it causes physical disabilities of motor functions and facial palsy [2]. These physical impairments sometimes continue with life of the survivors, thus affecting the quality of life of the patients. Long-term rehabilitation of such patients is required to recover fully or partially from this chronic attack [3]. The effective rehabilitation process hepse the patients to return to their normal life. According to [4] almost 80% of stroke patients suffer from motor movement dysfunction completely or to some extent, depending upon the severity of the cerebral attack.

Careful and accurate assessments of such dysfunctions are very pivotal for a patient's recovery [5]. Healthcare professionals such as doctors and physiotherapists are the only domain experts to recognize such deterioration in the movements of patients according to some benchmark criteria e.g. NIHSS or Fugl Meyer assessments [6]. Presently, the rehabilitation process is carried out at healthcare centers to monitor patient recovery. However, recent advancements in AI allow the use of an intelligent robotic-assisted system for the rehabilitation of patients from this chronic disease [7]. The use of such technologies allows the telerehabilitation of such chronic ailments at home. However the efficacy of this automated system is questionable unless it qualifies the criteria, that is to accurately recognize the pattern/ movements as identified by healthcare professionals [8]. This autonomous rehabilitation system can be built using two state-of-the-art techniques, signal-based methods using wearable sensors and computer vision algorithms [9]. It is particular to mention that the use of low-cost RGB cameras to monitor and analyze the patient's movements will be beneficial for healthcare professionals [10].

In this paper, we aim to develop an AI-based system that monitors and later on provides assessment for stroke patients according to the stroke scoring scale published by NIH America. This autonomous system will give the feedback of upper extremity motor functions. Enabling patients to be able to assess their conditions remotely using this technology. This application will help to overcome the shortage of dedicated healthcare professionals. During this development process, we used a smartphone to capture the video feed and then ran the human pose extraction algorithm to extract the keypoints of the patient's body joints. These extracted features are processed and passed to our machine learning classifier i.e. SVM, RF, and MLP. The classifier will provide the assessment of the patient's rehabilitation process, whether he/ she is getting improvements or needs to correct their exercise routines.

The paper is organized as follows. Related work in Section II, presents a brief comparison of available techniques and relevant studies. Section III explains the work methodology, data collection process, feature extraction, and data description. Then we discussed the results and conclusion.

Figure 1: Different signs of ailments in stroke patients

II. RELATED WORK

Human activity recognition emerged as a top-notch application of computer vision. It has a wide range of applications spanning from healthcare to autonomous coaching systems. Many scientists and researchers are developing useful systems using these algorithms. Especially the area of autonomous healthcare systems getting popular day by day. A lot of research work is going on to improve the healthcare systems and also to burden the health professionals. The area of stroke rehabilitation is also getting highlighted as it demands AI-based systems to come and play their role in building autonomous rehab applications so that patient can do their rehab at home even in the absence of physiotherapists [11]. Despite these advancements, these AI systems lack the standardization required for clinical adaptation.

Lee et al [12] utilize the power of VR technology to build an application for the rehabilitation of upper motor movements. First, they fused motion trajectories, performance, and evaluation measures to build multi-modal data. Then successfully trained the K-means clustering algorithms to effectively utilize the dataset. They termed their technique as an evidence-based method. Ultimately, the integration of diverse data sources significantly enhanced the machine learning model's performance, achieving an impressive accuracy rate of 92.72%. The outcome of their applications makes it feasible for clinical usage. However, the drawback of this work is that it is only limite to the virtual reality dataset.

Jung et al [13] develop an AI-based system to assess the severity of spasticity in upper extremity motor joints of post-stroke survivors. Four sets of exercises were performed by the patient to assess different joint SS scores. They used wearable sensors like inertial sensors to measure the kinematics of the patient's movements. The captured features using these sensors are passed to a machine learning classifier that predicts the value of severity of sparsticity of each body joint. Their published results exhibit that algorithms reasonably measure the upper motor movements to correlate these movements with spasticity of body joints. The overall process was a good effort but it needs to mount the sensors over different parts of the patient's body which can cause discomfort to the patient.

Rahman et al [14] used the PRISMA technique to analyze the use of AI-assisted virtual reality method for post-stroke survivors. They utilized UI-PRMD and KiMORE datasets to train and test their technique before clinical experiments. They efficiently utilized the dynamic attention mechanism on the spatiotemporal input features and achieved an RMSE of around 0.55 which is a good indicator. Their experiment is still under process and they have not yet deployed their algorithm for clinical trials or in reality.

Chung et al [15], proposed the use of virtual reality for upper-limb motor movement training in post-stroke survivors. A total of 20 patients participated in this experiment. They captured the motor features from a virtual avatar. Analyzed the relationship of these VR-extracted features with actual motor movement data of stroke survivors. These extracted features are then passed to a machine learning classifier to predict the assessment condition of the stroke patient. Significant improvements were observed during the prediction of the patient's movements, according to benchmark criteria like FMA, TEMPA, and WMFT. Several motor indicators showed a strong correlation with the actual patient data. Ultimately they achieved an accuracy of up to 86%.

III. METHODOLOGY

The resreach work was completed in two phases; training and testing of machine learning classifier using publically available benchmark datasets of stroke survivors, in the later phase a limited trial on patients and volunteers were conducted in the presence of physiotehrapists. The subsequent sections explains the overall working methodlogy of our research work.

A. Phase I: Model Development

Deep convolutional neural networks (CNNs) facilitate the creation of human pose estimation (HAR) algorithms, which are tailored for analyzing spatial information in images [16]. HAR algorithms can detect and interpret spatial patterns in images to determine whether a person is standing, sitting, falling, or lying down. These methods often predict the positions of a person's joints or body parts [17]. These algorithms help to build AI assisted applications to assess or improve the posture, angle and joint positions for a sportsman, a worker and also for patients.

B. UI-PRMD and TRSP Datasets

Out of publicly available benchmark datasets two were used in this research study UI-PRMD [18] and TRSP [19] published by University of Idahio and Toronoto rescpectively used to train the machine learning model. These datasets contains the human skeleton keypoints captured using Microsoft Kinect and Optical VICON sensors. These extracted feaures are saved in the form of spatial keypoints of consective frames in CSV files. The former dataset 10 healthy volunteers performed the exercises in both correct and incorrect manner in the presence of healthcare professional. In TRSP dataset overall of 19 partcipants 9 were stroke survivors and 10 were volunteers. They performed the upper body exercises using 2-DOF haptic robot. From these two datasets we only extracted the exercise data of upper extremity motor functions. These movements were carefully selected so that these conforms to the motor movemenst with NIHSS arm motor movements.

C. SPVD Datasets

It is our own developed dataset [20], created with help of physiotherapists. A total of 23 participated in the data collection process out of which 11 are stroke survivors and 12 are volunteers that performed the scripted task as demanded by NIHSS for assessment of stroke patients. The dataset has 10 classes of actions. It contains video recording of about 8.3 hours. These raw video clips are further pre-processed and cut to clips of 10 seconds for each class exercise. These videos are augmented to enhance the dataset.

$$T.D = O.D + A.D \tag{1}$$

$$A.D = Aug\ (\sigma, \mu) \tag{2}$$

Where T.D, O.D and A.D represent the total data, original data and the augmented data, respectively. The augmentation of data is carried out using random variables, with 'Aug' being the random augmentation function that achieved optimum result with mean value of 0 and a standard deviation of 0.05.

D. Mediapipe Pose for Feature Extraction

For this rehabilitation experimental study, we employ skeleton-based methodologies for human pose estimation, which identify significant key points of human body parts. Mediapipe follows a two-step mechanism.

First, it detects the person, and then it calculates the pose. In the initial phase, it identifies the spatial key points of the human body in an image using ConvNets. In the subsequent phase, it utilizes the Kalman filter to combine the temporal information of these key points. Mediapipe [21] identifies 33 landmarks in RGB video frames, as illustrated in Figure 2.

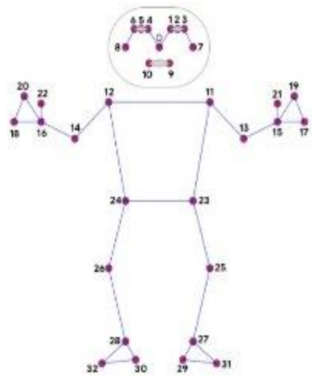

Figure 2: Body keypoints extracted by Mediapipe Pose

By forecasting two additional virtual key points, it conceptualizes the human body as a circle regarding its center, movement, and size. Consequently, it determines the relationship between the shoulder angle and the body's circumference radius. By streamlining the pose estimation procedure, Mediapipe enhances its capability to identify the dynamic interactions among different joints in the human body. The inclusion of virtual key points improves the model's accuracy and strengthens the human pose representation, enhancing the overall effectiveness and reliability of the real-time 2D pose estimation system.

E. Sliding Window Technique

For our machine learning classifiers, sliding window techniques are used to capture the temporal information of sequential data [22]. Human body key points are extracted using a pose estimation algorithm, and the sliding window processes this video data in sequence. By combining the capabilities of HPE algorithms, sliding windows, and ML classifiers, an algorithm can be developed to recognize activities in video frames. Typically, a video is divided into overlapping segments, and key points are extracted using windows in these overlapping areas. The following equation is used to calculate the number of windows W_S needed to cover the entire sequence of frames F_N:

The total number of sliding windows can be calculated using the following equation:

$$W_S = \left\lfloor \frac{F_N - S_F}{S_T} \right\rfloor \qquad (3)$$

Where S_F is the number of frames in each window, and S_T is the stride, which determines how many frames the window moves with each step. The floor function is used to round down to the nearest integer. For instance, with 50 video frames at 20 FPS, a window size S_F of 20, and a stride S_T of 10, the number of windows would be 4. Each window spans multiple video frames, thus capturing key point features and information related to patient activity within those frames.

F. Machine Learning Classifiers for Rehabilitation Assessment

At the end of our development pipeline, we used SVM, KNN, MLP, and RF as machine learning classifiers. We tried four different models for our prediction process which take the skeleton keypoints data and serve as input elements in the training of a model, a variety of classifiers are utilized, to predict patient movement sequences as per NIHSS [23]. After that, we have a scoring mechanism that will assess these motor movements according to NIHSS criteria.

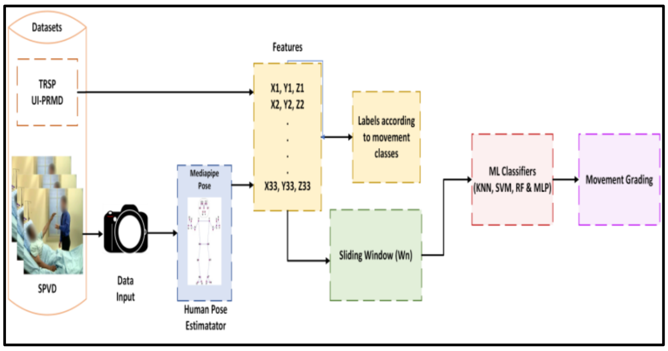

Figure 3: Stroke Patient Movement Assessment Pipeline

IV. RESULTS

A. Experimental Setup

To train the model, a Colab Pro account equipped with a V100 GPU was utilized. Three datasets were employed for model training, with each dataset divided into 70% for training and 30% for testing.

B. Motor Movements TRSP Dataset Results

The Toronto Rehab Stroke Posture (TRSP) [19] dataset features upper body sitting movements of stroke survivors. It includes CSV files documenting rehabilitation movements performed by 9 stroke survivors and 10 volunteers. The data is organized into directories based on left and right-hand movements, patient IDs, and labels assigned by physiotherapists. The dataset covers upper body movements such as shoulder elevation, trunk rotation, no compensation, and lean-forward. It provides 3D coordinates of 10 human skeleton landmarks, captured at 30 FPS. While the dataset contains useful examples, preprocessing involved only normalizing the data to a [0,1] scale for faster computations and checking for NaN values.

For classification, machine learning classifiers such as SVM, KNN, RF, and MLP were initially used to categorize the rehabilitation movements based on expert-assigned labels. The performance of each classifier is presented through accuracies and F1-scores, in Table 1.

C. Motor Movements UI-PRMD Dataset Results

The University of Idaho – Physical Rehabilitation mov-

Table 1: TRSP Dataset Results with Machine Learning Models

Classifier	**Class 0**		**Class 1**		**Class 2**	
	F1-Score	Accuracy	F1-Score	Accuracy	F1-Score	Accuracy
KNN	88.46	**96.96**	83.81	**96.96**	84.12	**96.96**
SVM	79.05	83.80	72.81	83.80	72.22	83.80
MLP	85.65	**96.87**	83.68	**96.87**	82.44	**96.87**
RF	88.54	**98.22**	87.68	**98.22**	86.58	**98.22**

-ement Dataset (UI-PRMD) [18] contains a collection of rehabilitation activities commonly performed during rehab programs and is publicly available. It features 10 healthy volunteers, each performing 10 different physical therapy movements, captured using VICON and Kinect sensors. The dataset is organized into CSV files, categorized into joint positions and angular files of the full body, annotated by experts. Notably, only five rehab exercises related to upper body movements were used, aligning with the NIHSS motor function examination tasks.

For preprocessing, similar techniques were applied, including normalization to speed up classifier convergence and checking for and eliminating NaN values to ensure data accuracy. Subsequently, a set of machine learning classifiers, including SVM, KNN, RF, and MLP, was used to classify the activities performed by the participants, the results are presented in Table 2.

Table 2: UI-PRMD Dataset Results with ML Models

Classifier	**Class 0**		**Class 1**	
	F1-Score	Accuracy	F1-Score	Accuracy
SVM	89.65	95.63	89.68	94.23
KNN	89.54	93.39	89.68	94.10
RF	91.62	95.60	93.49	**96.54**
MLP	90.05	**96.04**	89.81	95.21

D. Motor Movements SPVD Dataset Results

The Stroke Patient Motor Movements Dataset (SPVD) [20] consists of rehabilitation activities designed for evaluating stroke patients based on NIHSS criteria. Videos of 29 participants were recorded using an RGB camera at 30 FPS. To address the limitations of the original videos, data augmentation techniques were applied. The dataset is presented with spatiotemporal feature recordings, including the angles and positions of human body joints.

MediaPipe Pose [21] extracts key points of human joints from the RGB video. Initially, these skeleton features are pre-processed to handle empty frames by averaging the joint key points to predict any missing key points. Linear interpolation is used to calculate the missing key points.

After preprocessing the key points data, classical machine learning classifiers (SVM, KNN, RF, and MLP) are employed to classify stroke patient movements as per the NIHSS criteria. The performance of these ML models is evaluated, and presented in Table 3.

Table 3: SPVD Dataset Results with ML Models

Classifier	**Left Arm**		**Right Arm**	
	F1-Score	Accuracy	F1-Score	Accuracy
SVM	90.66	95.27	91.43	95.19
KNN	89.45	94.32	90.77	94.62
RF	91.83	**96.12**	91.75	**96.90**
MLP	89.41	93.47	90.40	95.94

V. CONCLUSION

This paper presented a classification pipeline that represents a significant milestone in developing a rehabilitation application for assessing upper body motor movements in stroke patients according to NIHSS guidelines. We successfully addressed the challenge of utilizing RGB camera video to create a real-time AI-augmented rehabilitation system, offering a non-invasive alternative to the discomfort associated with inertial sensors used in other methods. Our pipeline employed Mediapipe Pose to extract complex human skeletal joint data from a vast collection of video frames, efficiently utilizing the sliding window technique to pass this keypoint data sequentially to machine learning classifiers, including K-Nearest Neighbor (KNN), Support Vector Machines (SVM), Multilayer Perceptron (MLP), and Random Forest (RF). We also developed a scoring mechanism to grade these movements in accordance with the NIH stroke scale.

Looking ahead, we aim to explore advanced deep learning algorithms, such as LSTM and GRU networks, to further enhance the efficiency and accuracy of our assessment system. Additionally, we recognize the need to expand our assessment beyond upper extremity motor functions to encompass the full range of tasks outlined in the NIH stroke scale. This work lays the foundation for a more comprehensive and effective rehabilitation system for stroke survivors.

REFERENCES

[1] T. N. e. a. Rochmah, "Economic burden of stroke disease: a systematic review," *International journal of environmental research and public health,* vol. 18, no. 14, p. 7552, 2021.

[2] J. S. e. al., "Multidisciplinary care of patients with facial palsy: Treatment of 1220 patients in a German facial nerve center," *Journal of Clinical Medicine,* vol. 11, no. 2, p. 427, 2022.

[3] S. J. e. al., "MOG encephalomyelitis after vaccination against severe acute respiratory syndrome coronavirus type 2 (SARS-CoV-2): Case report and comprehensive review of the literature," *Journal of neurology,* vol. 269, no. 10, p. 5198–5212, Oct 2022.

[4] S. A. e. al., "Rehabilitation of upper limb motor impairment in stroke: A narrative review on the prevalence, risk factors, and economic statistics of stroke and state of the art therapies," *MDPI Healthcare,* vol. 10, no. 2, p. 190, Feb 2022.

[5] R. T. e. al., "Canadian stroke best practice recommendations: Rehabilitation, recovery, and community participation following stroke. Part one: Rehabilitation and recovery following stroke; update 2019," *International Journal of Stroke,* vol. 15, no. 07, p. 763–788, 2020.

[6] B. P. H. e. al., "Sensitivity to change and responsiveness of the upper extremity Fugl-Meyer assessment in individuals with moderate to severe acute stroke," *Neurorehabilitation and Neural Repair* , vol. 37, no. 8, p. 545–553, 2023.

[7] S. R. e. al., "AI-driven stroke rehabilitation systems and assessment: A systematic review," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 31, p. 192–207, 2022.

[8] L. Y. e. al., "Identifying stroke-related quantified evidence from electronic health records in real-world studies," *Artificial Intelligence in Medicine,* vol. 140, p. 102552, 2023.

[9] D. E. e. al., "Biosignal-based human–machine interfaces for assistance and rehabilitation: A survey," *Sensors,* vol. 21, no. 20, p. 6863, 2021.

[10] L. G. S. R. e. al., "Supervised classification of motor-rehabilitation body movements with RGB cameras and pose tracking data," *Journal on Interactive Systems,* vol. 13, no. 1, pp. 221-231, 2022.

[11] S. S. e. al., "Artificial intelligence for skeleton-based physical rehabilitation action evaluation: A systematic review," *Computers in Biology and Medicine,* vol. 158, p. 106835, 2023.

[12] L. L. M.-C. S. L. Z. a. S.-C. Y. J. Cui, "An evidence-based intelligent method for upper-limb motor assessment via a VR training system on stroke rehabilitation," *IEEE Access,* vol. 9, p. 65871–65881, 2021.

[13] Y. H. H. P.-C. H. S.-Y. Y. H.-T. L. Y.-C. C. a. B.-S. L. I.-J. Lee, "AI-based automatic system for assessing upper-limb spasticity of patients with stroke through voluntary movement," *IEEE Journal of Biomedical and Health Informatics,* vol. 28, no. 2, p. 742–752, 2022.

[14] S. S. A. K. M. N. H. M. M. U. M. F. I. a. S. D. S. Rahman, "AI-driven stroke rehabilitation systems and assessment: A systematic review," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 31, p. 192–207, 2022.

[15] M.-C. S. S.-H. L. E. H.-K. W. L.-H. T. a. S.-C. Y. C.-R. Chung, "An intelligent motor assessment method utilizing a bi-lateral virtual-reality task for stroke rehabilitation on upper extremity," *IEEE Journal of Translational Engineering in Health and Medicine,* vol. 10, p. 1–11, 2022.

[16] M. M. I. e. al, "Human activity recognition using tools of convolutional neural networks: A state of the art review, data sets, challenges, and future prospects," *Computers in biology and medicine* , vol. 149, p. 106060, 2022.

[17] M. G. F. C. a. C. F. F. C. F. G. Aquino, "Explaining one-dimensional convolutional models in human activity recognition and biometric identification tasks," *Sensors,* vol. 22, no. 15, p. 5644, 2022.

[18] H.-p. J. D. P. a. R. B. A. Vakanski, "A data set of human body movements for physical rehabilitation exercises," *MDPI Data,* vol. 3, no. 2, pp. 1-15, 2018.

[19] E. D. e. al., "The Toronto Rehab Stroke Pose dataset to detect compensation during stroke rehabilitation therapy," in *Proceedings of the 11th EAI international conference on pervasive computing technologies for healthcare*, 2017.

[20] W. A. a. U. M. T. Sherazi, "SPVD: A stroke patient motor movements video dataset for AI augmented rehabilitation," in *Proceedings of the 20th IBCAST,* Bhurban , 2023.

[21] V. B. e. al., *Blazepose: On-device real-time body pose tracking,* arXiv preprint, 2020.

[22] A. G. O. a. D. B. J. Ortiz Laguna, "A dynamic sliding window approach for activity recognition," in *Proc. 19th Int. Conf. User Modeling, Adaptation, and Personalization (UMAP 2011)*, Girona, Spain, 2011.

[23] P.-W. e. a. Chen, "Measuring activities of daily living in stroke patients with motion machine learning algorithms: A pilot study," *International journal of environmental research and public health* , vol. 18, no. 4, p. 1634, 2021.